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DOES LAND MARKETIZATION IMPROVE ECO-EFFICIENCY? EVIDENCE FROM CHINA

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Abstract. The trend of market-oriented land transaction scheme and the optimal allocation of land resources have become two important components of ecological sustainable development. However, the relevance of analyzing effects of land marketization on ecological and environmental development cannot be overemphasized. The ecological and environmental effects of land marketization are the focus of this paper. We begin by developing a theoretical framework to investigate how land marketization affects eco-efficiency. Moreover, we develop a data envelopment analysis model to measure eco-efficiency. We empirically investigate the effect of land marketization on eco-efficiency using a data set of 251 cities in China over the period of 2003 to 2018. Both theoretical and empirical results show that the land marketization exerts positive effects on eco-efficiency. Specifically, a 100% increase in land marketization level leads to a 2.4 percent increase in eco-efficiency. The heterogeneous effects and spatial effects of the land marketization on eco-efficiency are also examined. Besides, the endogeneity issues are also discussed using instrumental variable approach. Finally, the mechanism analysis shows that land marketization improves eco-efficiency primarily through improving efficiency change, best practice change and technology gap change, respectively. The main conclusions are confirmed by several robustness checks.

Keywords: land marketization, sustainable development, eco-efficiency, non-convex metafrontier, epsilon-based measure.

JEL Classification: C61, Q24, Q57, R14.

Introduction

In addition to stimulating capital accumulation and economic growth, land has long been regarded as the most significant economic resource in the world. Given that, a study of the process of land transaction marketization plays an important role in understanding the ecological sustainability development of the region. In addition, land markets are inextricably linked to land resources, and it is imperative to address the issue of protecting land resources

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as well as maintaining ecological balance, not only economic growth. As a result, land marketization cannot be underestimated in order to achieve sustainable development standards, which are seldom studied in existing literature.

Locally, however, it is an accepted fact that most prefecture-level cities have undergone and are continuing to experience rapid urbanization in China. As unavoidable consequences of urbanization, however, there exist undesirable effects such as imbalanced land use structures, significant distortions in land prices, and low land use efficiency. Due to these pressing and immediate problems, the traditional urban development model cannot be sustained, and Chinese urbanization requires urgent transformation. Therefore, reforming the land market and improving land marketization are essential steps to reach high-quality growth of the Chinese economy and ecological environment. Consequently, reforming the land market and improving land marketization are crucial to achieving high-quality economic growth and an ecological more sustainable environment in China.

The land marketization in China has been studied extensively, which will improve economic growth[1] (Li, 2014; Gao, 2019), the land use efficiency (Jiang et al., 2021), land productivity (Yao & Wang, 2022), and the allocative efficiency of the land (Wang & Tan, 2020). Furthermore, the accelerated marketization of Chinese land will lead to a reduction in pollution emission intensity (Du & Li, 2021). Land marketization has been studied separately in the literature for its economic and environmental effects, to the best of our knowledge, there is relatively little research on how land marketization might affect both at the same time. A particular focus needs to be given to the effects of land marketization on eco-efficiency[2], particularly in developing countries.

We examine how land marketization affects eco-efficiency in China. Towards this end, we develop a theoretical framework that investigates the impact of land marketization on eco-efficiency. And then measure eco-efficiency using an extend non-convex metafrontier data envelopment analysis (DEA) model, which is simultaneously incorporated non-convex metafrontier (Afsharian, 2017; Walheer, 2018; Jin et al., 2020), super efficiency (Andersen & Petersen, 1993), along with undesirable outputs into epsilon-based measure (EBM) (Tone & Tsutsui, 2010), namely, NCMeta-US-EBM. We further develop the Malmquist-Luenberger model based on NCMeta-US-EBM to decompose the eco-efficiency and derive the mechanism variables, that is, efficiency change, best practice change, and technology gap change. The improvement of eco-efficiency is an institutionalized goal in many cities, and it is recognized nationally as well. Land marketization has resulted in substantial economic growth and reduction of environmental pollution. Thus, land marketization is predicted to increase eco-efficiency directly or indirectly. Specifically, the land marketization may affect eco-efficiency through three channels and mechanisms.

While the literature has discussed the effect of land marketization on economic outcome and land use efficiency, there hasn't been a comprehensive analysis from a comprehensive viewpoint. Our main focus is that how and through which channels land marketization af-

[1] A municipal government's land acquisition strategy is motivated by their desire to maximize long-term economic growth and profit (Liu et al., 2016).

[2] To comprehensively consider both the economic and environmental impacts of cities, the World Business Council for Sustainable Development introduced a concept of eco-efficiency (Schmidheiney, 1993). It allows for the measurement of green growth levels as well as environmental quality (Yu et al., 2022).

fects eco-efficiency. This study makes the following contributions: first, we develop a theoretical model to investigate how land marketization affects eco-efficiency. Second, a DEA model is proposed for measuring eco-efficiency. Unlike a single factor analysis, the concept of eco-efficiency is based on the nexus between the environment and economic growth. Third, we empirically examine how land marketization affects eco-efficiency at the city level using the mediation effect model. Finally, we ascertain the spatial effects and distance decay effects of the land marketization on eco-efficiency using the spatial econometrics model proposed by Vega and Elhorst (2015), which seldomly considered in previous studies.

Our theoretical model shows that the land marketization is positively associated with eco-efficiency. Empirically, we find that the land marketization exerts significantly and positively effects on eco-efficiency. In addition, this study sheds light on some of the roles that land marketization plays in eco-efficiency growth. Besides, heterogeneous effects and spatial effects of land marketization on eco-efficiency are also investigated. We also find that our results are robust to alternative measures of eco-efficiency and land marketization, specification of econometric models, and instrumental variable estimation. Moreover, our study demonstrates the important role of land marketization in the description of eco-efficiency that is completely overlooked in the existing literature.

The reminder of this paper is arranged as follows. The theoretical model is presented in Section 1. The methodology and data are provided in Section 2. Empirical results and mechanisms analysis are presented in Sections 3 and 4, respectively. The last section concludes the paper.

1. Theoretical model

Following the existing studies (Baumol & Oates, 1998; Lin & Liu, 2008), we construct a theoretical model to ascertain the nexus between land marketization and eco-efficiency. For simplicity, we state the following assumptions. First, there are I administrative regions (jurisdictions) in a city, and each administrative region concentrates on producing a class of commodities X_i, and no matter what kind of commodities are produced, three elements need to be used: capital stock (K), land (T) and labor force (L). It is also assumed that the producers of commodity X_i are all price acceptors in the market. Besides, capital can interregional and intraregional flow, and every administrative area is the recipient of capital price. Second, in a certain period, the number of labor force remains unchanged in a specific administrative region, the labor market is a completely competitive market, and the working hours of labor force are also certain. Third, the nature of land use can be freely changed. The form of production function is specified as $Y = F(K, T, L)=K^{\alpha}T^{\beta}L^{1-\alpha-\beta}$. Though the production function is assumed to be in the form of constant returns to scale, our theoretical results are not depending on this assumption.

Having clarified the assumptions, we then theoretically derive the effects of land marketization on eco-efficiency. Divide both sides of production function by L at the same time, and the expression of per capita output can be obtained:

$$y = f(k, t), \tag{1}$$

where, $y = K/L$, $k = K/L$, $t = T/L$.

Given that, the marginal products of capital, land and labor are given by

$$\frac{\partial y}{\partial k} = f_k'(k,t); \tag{2}$$

$$\frac{\partial y}{\partial t} = f_t'(k,t); \tag{3}$$

$$\frac{\partial y}{\partial l} = f(k,t) - kf_k'(k,t) - tf_t'(k,t). \tag{4}$$

This study investigates the effect of land marketization on the ecological environment when local governments choose to increase land transfer to promote economic growth, consider residents' consumption well-being and maximize residents' well-being as the goal of land transfer. If the number of labor force in each administrative region i included in the city is fixed, and if the government pays all the land transfer fees to the labor force in the form of subsidies, the labor force wage in the i administrative region can be expressed as: $w_i = f(k,t) - k^i f^i_{k^i}(k^i, t^i)$.

Because the number of labor force contained in each administrative region of a city is constant, and the labor force obeys the hypothesis of homogeneity, the welfare utility level of labor force in each administrative region depends on its consumption level and per capita land possession, i.e., $U = U(c, t)$, where c denotes consumption. When urban land is used for economic production activities, it will have an impact on other land use needs of urban residents, such as residence and green land, and will bring negative utility, that is, $U_t(c,t)$ should be negative.

Besides the wage, the welfare of residents also needs to consider the influence of environmental pollution. We suppose that pollution has a geographical cross-border effect, so the local environmental damage comes from the local and neighboring pollution emissions at the same time. The pollution equation is an increasing convex function.

$$f(e,e^*) = \frac{(e+\delta e^*)^2}{2}, \tag{5}$$

where, e and e^* represents the pollution emissions of local and neighboring areas, respectively. δ measures the proportion of local pollutants in local environmental quality damage, ranging from 0 to 1, $\delta = 0$ indicates all local environmental damage comes from local pollution discharge while $\delta = 1$ indicates all the local environmental damage comes from other areas.

Assuming that the income of urban residents includes two parts, namely wage income (w) and other income (ϖ). Given that, following previous studies (Lin & Liu, 2008; Caliendo & Parro, 2015), the utility maximization objective function of urban residents is given by

$$\begin{aligned} &\max \quad U = U(c,t) - \frac{(e+\delta e^*)^2}{2} \\ &\text{s.t.} \;\; c = w + \varpi, \\ &\qquad 0 \le \delta \le 1. \end{aligned} \tag{6}$$

And the first-order conditions that can maximize the consumption utility of urban residents are as follows: $-\dfrac{U_t(c,t)}{U_c(c,t)} = f_t'(k,t)$, and $f_k'(k,t) = r$.

Furthermore, the optimization model for maximizing the total social utility is as follows

$$
\begin{aligned}
\max \quad & U^j = U^j(c^j, t^j) - \frac{(e+\delta e^*)^2}{2} \\
\text{s.t.} \quad & U^i(c^i, t^i) = U_0^i \ (i = 1, 2, \cdots, I \text{ and } i \neq j) \\
& \sum_{i=1}^{I} s^i f^i(k^i, t^i) = \sum_{i=1}^{I} s^i c^i, \\
& \sum_{i=1}^{I} s^i k^i = \frac{K}{\sum_{i=1}^{I} L^i}, \\
& 0 \le \delta \le 1,
\end{aligned}
\tag{7}
$$

where, superscript i represents the ith jurisdiction in a specific city. f^i is the per capita output of residents in the ith jurisdiction. c^i is the consumption level of residents in the ith jurisdiction. s^i represents the share of the ith jurisdiction the urban social labor force. k^i represents the share of the ith jurisdiction the urban social capital stock.

Under the condition that the utility level of residents in other administrative areas is kept at a certain level, that is, U_0^i, the representative residents' consumption welfare utility is maximized, that is, the optimal solution is $-\frac{U_t^i(c,t)}{U_c^i(c,t)} = f_t^i(k_i, t_i)$, and $f_k^i(k,t) = f_k^j(k,t) = r$.

The equation $-\frac{U_t^i(c,t)}{U_c^i(c,t)} = f_t^i(k_i, t_i)$ indicates that if all the land income is returned to the residents in the form of subsidies, any amount of incremental urban land supply can improve the residents' utility level, and the local government can attract capital investment by increasing the land supply, thus promoting the decision-making of urban economy, and improving the residents' utility.

However, suppose that the distribution ratio of urban land transfer fee obtained by urban residents is ρ (which measures the magnitude of land marketization). Given the above, the first-order conditions for maximizing the utility of urban residents are as follows

$$-\frac{U_t(c,t)}{U_c(c,t)} = \rho f_t'(k,t) - (1-\rho) t f_{tt}''(k,t), F_K = r. \tag{8}$$

With $-tf_{tt}''(k,t) = (1-\alpha) f_t'(k,t)$, thus

$$-\frac{U_t(c,t)}{U_c(c,t)} = \rho f_t'(k,t) + (1-\rho)(1-\alpha) f_t'(k,t) = [1-(1-\rho)\alpha] f_t'(k,t). \tag{9}$$

Compared to $-\frac{U_t^i(c,t)}{U_c^i(c,t)} = f_t^i(k_i, t_i)$, it is not difficult to find that the higher the local government's distribution ratio (1 – ρ) in the income of urban land leasing, and the greater the elasticity of urban land output α, the larger the gap between the urban land transfer amount and the transfer amount required by residents' utility maximization.

Furthermore, according to the index measurement formula of production efficiency:

$$ee = \frac{\sum \mu_r y_r}{\sum u_m x_m}, \tag{10}$$

where, y_r, x_m are the rth output and the mth input variables, μ_r and u_m are the corresponding weight, respectively. According to the previous theoretical derivation, the numerator is the total output $F(K,T,L)$, and the denominator includes capital stock, land, and labor force, and we have

$$ee = \frac{F(K,T,L)}{u_1 K + u_2 T + u_3 L} = \frac{f(k,t)}{u_1 k + u_2 t + u_3}. \tag{11}$$

Thus,

$$\frac{\partial ee}{\partial \rho} = \frac{U_t(c,t)}{U_c(c,t)} \times \frac{\alpha}{[1-(1-\rho)\alpha]^2} \times \frac{1}{u_1 k + u_2 t + u_3} > 0. \tag{12}$$

Consequently, the magnitude of land marketization imposes a positive impact on eco-efficiency.

2. Methodology and data

2.1. Measuring for eco-efficiency

Assuming that there is a total of N decision making units (DMUs), $G(G>1)$ heterogeneous technology groups and N_g DMUs in Group g, we have $\sum_{g=1}^{G} N_g = N$. Each DMU generates desirable (good) outputs $\mathbf{y} = \left[y_1, y_2, \cdots, y_R\right] \in \Re_+^R$ and undesirable (bad) outputs $\mathbf{b} = \left[b_1, b_2, \cdots, b_J\right] \in \Re_+^J$ by using inputs $\mathbf{x} = \left[x_1, x_2, \cdots, x_M\right] \in \Re_+^M$. Under the variable returns to scale (VRS) assumption and the group frontier framework, the production technology of the o^{th} DMU in Group g (o = 1, 2, …, Ng, g =1, 2, …, G) can be defined as follows:

$$\begin{aligned} P^g = \Big\{(\mathbf{x}_m, \mathbf{y}_r, \mathbf{b}_j) : & \sum_{n\in g', n\neq o \ if \ g=g'} \lambda_{gn} x_{mgn} \le x_{mg'o}, m = 1,2,\cdots,M, \\ & \sum_{n\in g', n\neq o \ if \ g=g'} \lambda_{gn} y_{rgn} \ge y_{rg'o}, r = 1,2,\cdots,R, \\ & \sum_{n\in g', n\neq o \ if \ g=g'} \lambda_{gn} b_{jgn} \le b_{jg'o}, r = 1,2,\cdots,J, \\ & \sum_{n\in g', n\neq o \ if \ g=g'} \lambda_{gn} = 1; \lambda_{gn} \ge 0, \\ & g = 1,2,\cdots,G; n \in g', n \neq o \ if \ g = g' \Big\}, \end{aligned} \tag{13}$$

where λ_{gn} is a weighting vector for the n^{th} DMU and Group g. Following Battese et al. (2004), the non- convex metafrontier production technology can be encompassed by all group frontier technologies, and it can be expressed as follows:

$$\begin{aligned} P^{nc-meta} = \Big\{(\mathbf{x}_m, \mathbf{y}_r, \mathbf{b}_j) : & \sum_{g=1}^{G} \sum_{n\in g', n\neq o \ if \ g=g'} \xi_{gn} x_{mgn} \le x_{mg'o}, m = 1,2,\cdots,M, \\ & \sum_{g=1}^{G} \sum_{n\in g', n\neq o \ if \ g=g'} \xi_{gn} y_{rgn} \ge y_{rg'o}, r = 1,2,\cdots,R, \end{aligned}$$

$$\sum_{g=1}^{G}\sum_{n\in g',n\neq o \text{ if } g=g'}\xi_{gn}b_{jgn}\leq b_{jg'o}, j=1,2,\cdots,J,$$
$$\sum_{g=1}^{G}\sum_{n\in g',n\neq o \text{ if } g=g'}\xi_{gn}=1;\xi_{gn}\geq 0,$$
$$g=1,2,\cdots,G; n\in g',n\neq o \text{ if } g=g'\Big\}, \quad (14)$$

where $P^{nc-meta}=\left\{P^1\cup P^2\cup\cdots\cup P^G\right\}$ and ξ_{gn} is a weighting vector for the n^{th} DMU and Group g. As a result, the optimal solution for the o^{th} DMU in Group g (o = 1, 2, …, Ng, g =1, 2, …, G) can be estimated as:

$$\rho_{go}^{*}=\min\frac{\theta-\varepsilon^{-}\dfrac{1}{\sum_{m=1}^{M}\omega_{mgo}^{x}}\sum_{m=1}^{M}\dfrac{\omega_{mgo}^{x}s_{mgo}^{x}}{x_{mgo}}}{\eta+\varepsilon^{+}\dfrac{1}{\sum_{r=1}^{R}\omega_{rgo}^{y}+\sum_{j=1}^{J}\omega_{jgo}^{b}}\left(\sum_{r=1}^{R}\dfrac{\omega_{rgo}^{y}s_{rgo}^{y}}{y_{rgo}}+\sum_{j=1}^{J}\dfrac{\omega_{jgo}^{b}s_{jgo}^{b}}{b_{jgo}}\right)}$$

$$\text{s.t. } \theta x_{mg'o}-\sum_{n\in g',n\neq o \text{ if } g=g'}\lambda_{gn}x_{mgn}+s_{mg'o}^{x}\geq 0, m=1,2,\cdots,M,$$
$$\sum_{n\in g',n\neq o \text{ if } g=g'}\lambda_{gn}y_{rgn}-\eta y_{rg'o}+s_{rg'o}^{y}\geq 0, r=1,2,\cdots,R,$$
$$\eta b_{jg'o}-\sum_{n\in g',n\neq o \text{ if } g=g'}\lambda_{gn}b_{jgn}+s_{jg'o}^{b}\geq 0, j=1,2,\cdots,J,$$
$$\sum_{n\in g',n\neq o \text{ if } g=g'}\lambda_{gn}=1,$$
$$\lambda_{gn},s_{mg'o}^{x},s_{rg'o}^{y},s_{jg'o}^{b}\geq 0; 0<\theta\leq 1;\eta\geq 1,$$
$$0\leq\varepsilon^{-},\varepsilon^{+}\leq 1; 0<\omega_{mgo}^{x},\omega_{rgo}^{y},\omega_{jgo}^{b}\leq 1.\Big\}, \quad (15)$$

where $x_{mg'o}$, $y_{rg'o}$, and $b_{jg'o}$ are the inputs, desirable outputs, and undesirable outputs of the unit $\text{DMU}_{g'o}$, and the corresponding slacks are denoted by $s_{mg'o}^{x}$, $s_{rg'o}^{y}$, and $s_{jg'o}^{b}$, respectively.

The efficiency measures radial and non-radial, heterogeneous technology, and undesirable outcomes are considered simultaneously. Given that, the EBM model (Tone & Tsutsui, 2010) is extended to the NCMeta-US-EBM model. Under the VRS assumption and the non-convex metafrontier framework, the optimal solution for the o^{th} DMU and Group g (o = 1, 2, …, Ng, g =1, 2, …, G) is estimated as:

$$\rho_{go}^{nc-meta*}=\min\frac{\theta-\varepsilon^{-}\dfrac{1}{\sum_{m=1}^{M}\omega_{mgo}^{x}}\sum_{m=1}^{M}\dfrac{\omega_{mgo}^{x}s_{mgo}^{x}}{x_{mgo}}}{\eta+\varepsilon^{+}\dfrac{1}{\sum_{r=1}^{R}\omega_{rgo}^{y}+\sum_{j=1}^{J}\omega_{jgo}^{b}}\left(\sum_{r=1}^{R}\dfrac{\omega_{rgo}^{y}s_{rgo}^{y}}{y_{rgo}}+\sum_{j=1}^{J}\dfrac{\omega_{jgo}^{b}s_{jgo}^{b}}{b_{jgo}}\right)}$$

$$\text{s.t. } \theta x_{mg'o} - \sum_{g=1}^{G} \sum_{n\in g', n\neq o \text{ if } g=g'} \xi_{gn} x_{mgn} + s_{mg'o}^{x} \geq 0, m = 1,2,\cdots,M,$$
$$\sum_{g=1}^{G} \sum_{n\in g', n\neq o \text{ if } g=g'} \xi_{gn} y_{rgn} - \eta y_{rg'o} + s_{rg'o}^{y} \geq 0, r = 1,2,\cdots,R,$$
$$\eta b_{jg'o} - \sum_{g=1}^{G} \sum_{n\in g', n\neq o \text{ if } g=g'} \xi_{gn} b_{jgn} + s_{jg'o}^{b} \geq 0, j = 1,2,\cdots,J,$$
$$\sum_{n\in(g'=1), n\neq o \text{ if } g=g'} \xi_{gn} = \phi_1, \sum_{n\in(g'=2), n\neq o \text{ if } g=g'} \xi_{gn} = \phi_2, \cdots, \sum_{n\in(g'=G), n\neq o \text{ if } g=g'} \xi_{gn} = \phi_G,$$
$$\sum_{g=1}^{G} \phi_g = 1, \phi_g = 1 \text{ or } 0; \xi_{gn}, s_{mg'o}^{x}, s_{rg'o}^{y}, s_{jg'o}^{b} \geq 0,$$
$$0 < \theta \leq 1; \eta \geq 1; 0 \leq \varepsilon^{-}, \varepsilon^{+} \leq 1; 0 < \omega_{mgo}^{x}, \omega_{rgo}^{y}, \omega_{jgo}^{b} \leq 1. \Big\}, \tag{16}$$

where ε^- and ε^+ are the parameters indicate the importance of the non-radial part of the evaluation. $\omega_{mg'o}^{x}$, $\omega_{rg'o}^{y}$, and $\omega_{jg'o}^{b}$ represent the relative importance of inputs, desirable outputs, and undesirable outputs, respectively. If ε^- and ε^+ are equal to zero, both Models (15) and (16) degenerate to the radial measurements, and if ε^- and ε^+ are equal to one, they degenerate to the slacks-based measurements.

It is worth pointing out that the NCMeta-US-EBM model is different from the model proposed by Tone and Tsutsui (2010) as they did not consider non-convex metafrontier technology, undesirable outputs, and super efficiency. Although the DEA model which simultaneously considered metafrontier, super efficiency, and undesirable output in EBM has been proposed (Luo et al., 2022), however, the metafrontier considered in previous study is convex, indicating that the infeasible input-output combinations could not be further excluded. If so, the results may be biased. The main advantage of NCMeta-US-EBM is its exclusion of the infeasible input-output combinations. Given that, the eco-efficiency measures estimated by the proposed models are more accurate than the traditional DEA models.

2.2. Metafrontier-Malmquist model

The Malmquist index has been benchmarked globally through the metafrontier method and its decomposition (Oh & Lee, 2010). To determine whether the decrease in eco-efficiency over the years can be attributed to technological change (*TC*) or efficiency change (*EC*), we further compute the Malmquist-Luenberger index (Choi et al., 2015) to derive the mechanism variables. First, according to the group frontier, the global Malmquist index can be decomposed into

$$M_{global}^{group}(x^{t+1}, y^{t+1}, b^{t+1}, x^t, y^t, b^t) = \frac{E^{group}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{group}(x^t, y^t, b^t)}$$
$$= \frac{E^{group,t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{group,t}(x^t, y^t, b^t)} \times \left(\frac{\dfrac{E^{group}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{group,t+1}(x^{t+1}, y^{t+1}, b^{t+1})}}{\dfrac{E^{group}(x^t, y^t, b^t)}{E^{group,t}(x^t, y^t, b^t)}} \right)$$

$$= \frac{TE^{group,t+1}}{TE^{group,t}} \times \left(\frac{BPG^{group,t+1}}{BPG^{group,t}} \right)$$

$$= EC^{(t,t+1)} \times BPC^{(t,t+1)}, \tag{17}$$

where M_{global}^{group} defines the global Malmquist index of each group, E represents eco-efficiency measured by the proposed model. TE represents the technological efficiency. BPG, EC, and BPC denote the Best Practice Gap, the efficiency change, and the change in BPG.

Second, the non-convex metafrontier Malmquist index can be further decomposed based on Eq. (17) and defined as follows.

$$M_{global}^{nc-meta}(x^{t+1}, y^{t+1}, b^{t+1}, x^t, y^t, b^t) = \frac{E^{nc-meta}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{nc-meta}(x^t, y^t, b^t)}$$

$$= \frac{E^{group,t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{group,t}(x^t, y^t, b^t)} \times \left(\frac{\dfrac{E^{nc-meta}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{group,t+1}(x^{t+1}, y^{t+1}, b^{t+1})}}{\dfrac{E^{nc-meta}(x^t, y^t, b^t)}{E^{group,t}(x^t, y^t, b^t)}} \right)$$

$$= \frac{TE^{group,t+1}}{TE^{group,t}} \times \left(\frac{\dfrac{E^{group}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{group,t+1}(x^{t+1}, y^{t+1}, b^{t+1})}}{\dfrac{E^{group}(x^t, y^t, b^t)}{E^{group,t}(x^t, y^t, b^t)}} \right) \times \left(\frac{\dfrac{E^{nc-meta}(x^{t+1}, y^{t+1}, b^{t+1})}{E^{group}(x^{t+1}, y^{t+1}, b^{t+1})}}{\dfrac{E^{nc-meta}(x^t, y^t, b^t)}{E^{group}(x^t, y^t, b^t)}} \right)$$

$$= \frac{TE^{group,t+1}}{TE^{group,t}} \times \left(\frac{BPG^{group,t+1}}{BPG^{group,t}} \right) \times \left(\frac{TGR^{t+1}}{TGR^t} \right)$$

$$= EC^{(t,t+1)} \times BPC^{(t,t+1)} \times TGC^{(t,t+1)}, \tag{18}$$

where TGC denotes the Technology Gap Change.

2.3. Measuring for land marketization

Hybridity and institutional resilience are two significant characteristics of China's urban land market (Jiang & Lin, 2021), measuring land marketization has become a challenge. Following Fan et al. (2020) and Lu et al. (2020), our measure of land marketization in China is based on the weighted data from various administrative land transactions. Specifically, based on the detailed information on more than 2.32 million land transfers in China during 2001–2020, the land marketization is calculated as follows:

$$lm_{it} = \frac{\sum q_i p_i}{\sum q_i}, \tag{19}$$

where, lm_{it} is the land marketization for city i at year t, which ranges from 0 to 1; q_i is the amount of land that city i sold in the land market and p_i is the price weight of the land sold of city i.

Figure 1 depicts the land marketization in China from 2003 to 2018, indicating that China's land marketization trend was on the upswing during this period. It is clear that the land marketization remained at a low level until 2008, because of the new regulation on land

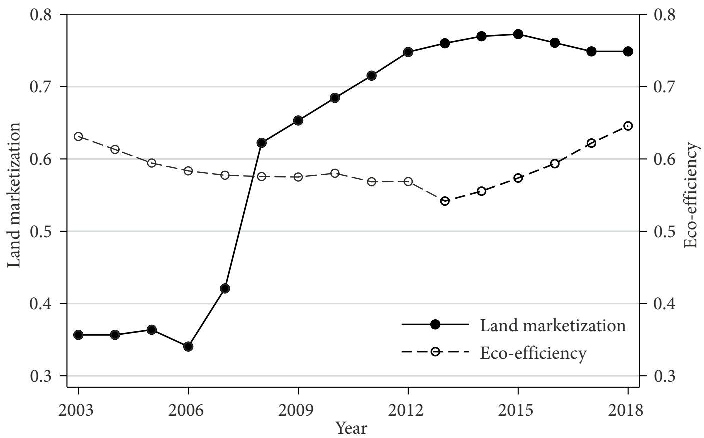


Figure 1. The trend of land marketization and eco-efficiency in Chinese cities during 2003–2018

market was subsequently extended in 2007 to cover the conveyance of industrial land (Jiang & Lin, 2021). More specifically, the land marketization grew dramatically after 2006, increasing from 0.340 in 2006 to 0.748 in 2012, an increase of nearly 2.2 times. After 2012, the land marketization increased steadily, reaching to 0.773 in 2015, and then dropped to 0.749 year by year. For comparison, we also present the national average of eco-efficiency and see how it evolved over the years. Evidently, the average value of eco-efficiency ranges from 0.5 to 0.7, indicating that there are 30–50% improvement room to reach the efficient frontier. In particular, the eco-efficiency level declined until 2013, and then rose quite rapidly ever since, indicating that the ecological environment quality has been greatly improved in recent years.

2.4. Empirical strategy

To estimate how land marketization impacts eco-efficiency in China, this study is primarily aimed at estimating the ecological effects of land marketization. Having measured the eco-efficiency and land marketization, we control city characteristics, city fixed effects and year fixed effects in the empirical model, which specified as:

$$ee_{ct} = \alpha + \beta lm_{ct} + \gamma x_{ct} + \lambda_c + \tau_t + \varepsilon_{ct}, \tag{20}$$

where ee_{ct} denotes the eco-efficiency for city c of year t; lm_{ct} is the land marketization for city c of year t; x_{ct} is a vector of control variables for city c of year t, including the scale effects, labor cost, technological innovation, industrial structure, which proxied by population size (*lnpop*), average wage of employees (*lnwage*), technological innovation index (*innovation*), and proportion of output value of secondary industry (*sind*). Theoretically, control variables are selected based on the IPAT equation (Stern et al., 1992) and its stochastic version STIRPAT (Dietz & Rosa, 1994). Empirically, the STIRPAT model is frequently used to investigate the determinants of eco-efficiency. Specifically, the demographic measurement is proxied by population size. We use the average wage of employees and technological innovation index to represent the affluence of residents and technology. Besides, we control economic structure which proxied by the proportion of secondary industry value added in GDP. λ_c and τ_t capture city and year fixed effects, respectively. ε_{ct} denotes the error term. α, β, γ are parameters need to be estimated. We predict that the land marketization exerts positive effects on eco-efficiency, i.e., $\beta > 0$. Thus, the null hypothesis in this study is H_0: $\beta > 0$.

To test the spatial effects of land marketization on eco-efficiency, a spatial lag term (Wlm_{ct}) is introduced into the baseline model, which specified as:

$$ee_{ct} = \alpha + \beta_1 lm_{ct} + \beta_2 Wlm_{ct} + \gamma x_{ct} + \lambda_c + \tau_t + \varepsilon_{ct}, \tag{21}$$

where W is the spatial weight matrix. Other notations are the same as Eq. (20). Specifically, to investigate the distance effect of land marketization on eco-efficiency, we create spatial weighting matrices with varying distance thresholds, which defined as:

$$\omega_{cd} = \begin{cases} \dfrac{1}{d_{cd}}, & \text{if } d_{cd} \le d_{threshold} \\ 0, & \text{if } d > d_{threshold} \end{cases}, \tag{22}$$

where $d_{threshold}$ denotes the distance threshold (km), ranging from 1442 km to 4400 km, and steps up by 50 km each time. This setting allows us to investigate whether the effects of the land marketization in the neighboring cities spread to a limited extent (local spatial spillovers) or not (global spatial spillovers).

2.5. Data and variables

The sample consists of 251 prefectures in China (2003–2018), and cities located in Tibet, Taiwan, Hong Kong, and Macau are excluded due to unavailability of data. Data was collected from several official sources, including China City Statistical Yearbooks (2004–2019), China Energy Statistical Yearbooks (2004–2019), and China Statistical Yearbooks (2004–2019).

For an accurate and comprehensive measurement of eco-efficiency, the following input and output variables are selected. The input variables include labor force, capital stock and energy consumption. First, based on the available data, the total number of employees at year-end is used to measure labor force. Second, the perpetual inventory method is adopted to calculate the capital stock (Wu et al., 2014; Huang et al., 2018). Third, primary energy consumption was estimated using the bottom-up approach proposed by Huang et al. (2018). This method is recently used by Jia et al. (2021), Yu and Zhang (2021), and Luo et al. (2021). Both desirable output and undesirable output are incorporated into the model. The GDP is chosen as the desirable output at constant prices (price base year = 2003) while the undesirable output consists of carbon emissions, which estimated by using the existing literature (Huang et al., 2018).

Table 1 presents descriptive statistics of the input and output variables (*Panel A*), dependent and independent variables (*Panel B*), and mechanism variables (*Panel C*) which calculated from Eq. (18). It is worth noting that the mean value of eco-efficiency is 0.587, indicating that the eco-efficiency has 41.3% (= (1–0.587) ×100%) room for improvement relative to the efficient frontier. The correlation between the dependent variable and independent variables is presented in Table 2, the maximum correlation coefficient is 0.466, indicating that there is no serious multicollinearity problem in our models.

Table 1. Summary statistics

Variables	Unit	Observations	Mean	Standard Deviation	Minimum	Maximum
Panel A. Input and output variables in DEA model						
labor force	10^4 persons	4016	54.254	78.660	5.490	986.870
capital stock	10^8 CNY	4016	2082.608	3023.037	27.775	37450.600
energy consumption	10^4 tce	4016	1566.801	1558.842	46.561	12100.000
gdp	10^8 CNY	4016	1447.582	2016.508	41.166	23766.990
carbon dioxide	10^4 tons	4016	4014.793	3966.043	125.591	28953.700
Panel B. Dependent and independent variables in econometric model						
ee	–	4016	0.587	0.160	0.187	1.056
lm	–	3883	0.620	0.296	0.000	1.000
lnpop	10^4 persons	4016	5.921	0.679	3.392	8.129
lnwage	10^4 CNY	4016	10.335	0.627	2.283	11.813
innovation	–	3514	0.078	0.412	0.000	10.614
sind	%	4016	48.649	10.789	14.950	90.970
Panel C. Mechanism variables in mediation analysis						
efficiency change	–	3765	0.999	0.080	0.406	1.962
best practice change	–	3765	1.006	0.063	0.528	1.380
technology gap change	–	3765	1.006	0.071	0.531	1.386

Note: CNY and tce represent Chinese Yuan and metric tons of standard coal equivalent, respectively.

Table 2. Correlation among dependent variables

	ee	*lm*	*lnpop*	*lnwage*	*innovation*
lm	0.059***	1.000			
lnpop	–0.101***	0.026	1.000		
lnwage	0.013	0.466***	0.038**	1.000	
innovation	0.107***	0.027	0.178***	0.264***	1.000
sind	–0.181***	0.058***	–0.201***	0.062***	–0.141***

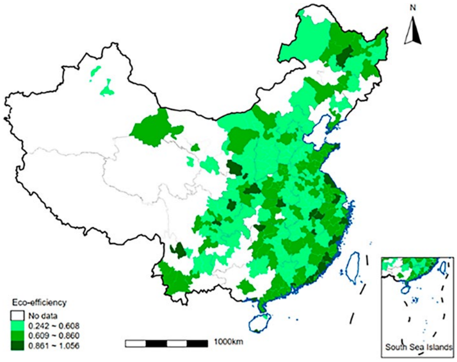
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3. Results and discussion

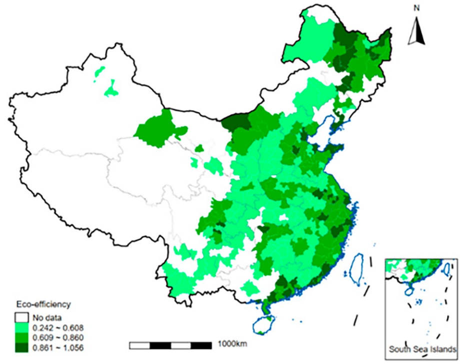
3.1. Stylized facts

Figure 2a and 2b present the spatial distribution of eco-efficiency for 2003 and 2018, and Figure 2c and 2d illustrate the spatial distribution of land marketization for the same years. Three stylized facts could be obtained. First, most cities in the central/western regions have low rates of eco-efficiency and land marketization levels, whereas cities along the eastern coast maintain high levels. The findings are consistent with Fan et al. (2020), in the south-eastern regions and the provincial capitals, researchers have found that land marketization

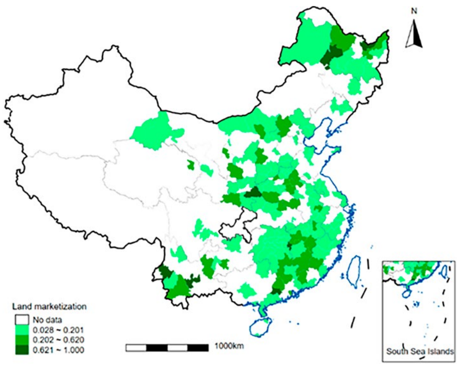
a) Spatial distribution of eco-efficiency in 2003



b) Spatial distribution of eco-efficiency in 2018



c) Spatial distribution of land marketization in 2003



d) Spatial distribution of land marketization in 2018

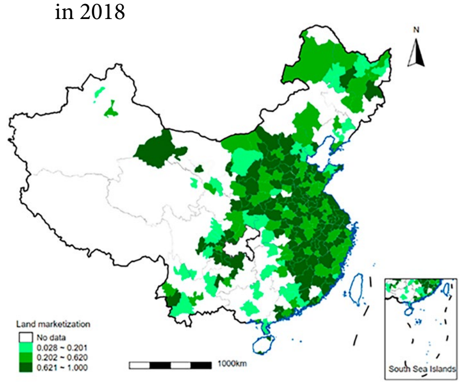


Figure 2. The spatial distribution of eco-efficiency and land marketization in China for 2003 and 2018

levels tend to be higher. Second, from 2003 to 2018, the eco-efficiency and land marketization levels have improved, especially for cities in the eastern region. Third, there may be a positive correlation between the land marketization level and eco-efficiency. However, we need further empirical analysis to confirm the claim and hypothesis using econometric analysis.

3.2. Baseline results

Based on various scenarios, Table 3 shows the impact of the land marketization on eco-efficiency. Specifically, column (1) shows the effects of land marketization on eco-efficiency without taking the control variables into consideration, while columns (2)–(5) show the regression results incorporating the control variables into the model one by one.

The results indicate an ecological sustainable development effect of the land marketization. Based on column (1), the coefficient of *lm* is significantly positive at the 5% level, indicating that the land marketization is conducive to increasing eco-efficiency. Specifically, the eco-efficiency has a 3.1% increase associated with a 100% increase in land marketization level, *ceteris paribus*. In addition, among other relevant factors, population size is negatively associated with eco-efficiency, which is in line with the studies of Luo et al. (2021) and Ren et al. (2018), which finds that population size deteriorates the eco-efficiency since the expansion of population increase resource consumption and worsens environmental quality. Another control variable worthy of our attention is innovation. Within our expectation, technological innovation exerts significantly and positively effects on eco-efficiency, indicating that technological innovation is conducive to improving eco-efficiency by approximately 3.7%. Given that, local governments should encourage firms to focus on strengthen technological progress and innovation, enhance the ability to convert investment scale to output scale the scale of investment into output scale, and promote the transformation and upgrading of low-efficiency firms in the region, thereby improving eco-efficiency. Besides, the higher the proportion of the secondary industry, the less conducive to the improvement of eco-efficiency, since the coefficient of *sind* is significantly negative associated with eco-efficiency. Therefore, it is necessary to change the industrial production structure and promote industrial upgrading. In addition to increasing the level of land marketization, the findings also indicate that policymakers should improve environmental quality of the cities with lower eco-efficiency through undertaking green industry transfer, enhancing technological innovation and upgrading industrial structure.

Table 3. The effects of land marketization on eco-efficiency

Variables	(1)	(2)	(3)	(4)	(5)
lm	0.031** (0.018)	0.031** (0.018)	0.031** (0.018)	0.032** (0.011)	0.024** (0.043)
lnpop		–0.053 (0.401)	–0.054 (0.383)	–0.050 (0.273)	–0.061 (0.156)
lnwage			–0.008 (0.591)	0.001 (0.913)	0.007 (0.451)
innovation				0.045*** (0.000)	0.037*** (0.001)
sind					–0.003*** (0.000)
constant	0.567*** (0.000)	0.881** (0.019)	0.968*** (0.009)	0.843*** (0.002)	1.014*** (0.000)
city fixed effects	YES	YES	YES	YES	YES
year fixed effects	YES	YES	YES	YES	YES
observations	3883	3883	3883	3383	3383
adjusted R-squared	0.815	0.816	0.816	0.846	0.854

Notes: (1) Robust p value in parentheses and robust standard error are clustered at the city level. (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.3. Heterogeneous effects

When evaluating the effect of a certain policy, policymakers may be interested in more than the average impact of the policy. Due to the specific characteristics of the sample cities, the effect of a macroeconomic activity on eco-efficiency may be heterogeneous across quantiles.

Consequently, the quantile regression is a feasible method to investigate such heterogeneous effects because the results of the method are robust and less sensitive to the heteroscedasticity and outliers.

Here we examine how land marketing improves eco-efficiency across different quantiles by examining its heterogeneity. Estimation coefficients of the key variable for different quantiles (from 0.1 to 0.9) are shown in Figure 3. The results suggest that the level of land marketization has a higher impact on cities with higher eco-efficiency than it has on cities with lower eco-efficiency. There is significant evidence that the results support the robustness of the baseline findings for different quantiles, i.e., the land marketization leads to improve eco-efficiency.

Based on cities geographical location, environmental regulation stringency, and resource endowments, the sample is divided into three groups (Yu & Zhang, 2019). First, eastern cities are generally at a more advanced level of economic growth, whereas their counterparts in the central and western and northeastern regions tend to perform worse economically. Using the first criterion, we divide all cities into three groups: 87 cities in eastern region, 144 cities in central and western regions, and 20 cities in northeastern region. Second, our sample can be divided into: 147 cities listed as two-control zones (TCZ) and 104 non-TCZ cities, the former is subject to more stringent environmental policies and standards. Third, we can divide all the cities into two groups: 101 cities listed as resource-based (RB) cities and 150 non-RB cities. Eco-efficiency evolves in different ways within these different groups, as shown in Figure 4. Evidently, the eco-efficiency of different cities has a trend of first decreasing and then increasing, showing a U-shaped change trend. Finally, the heterogeneous effects of land marketization on eco-efficiency are further investigated.

Estimation results are summarized in Table 4. The results suggest that the land marketization in the less developed central and western regions has a greater positive impact on eco-efficiency. The finding has very important policy implications. Although the eco-efficiency of the central and western regions is smaller than that of the eastern region, and the gap is widening year by year, the policymakers and practitioners in central and western regions can promote the improvement of eco-efficiency by optimizing the level of land marketization, and realize regional green transformation and sustainable development. Regarding the northeastern region, the estimated result of land marketization is not statistically significant. Compared to cities not nationally listed as TCZ, the TCZ cities are subject to more stringent environmental regulations typically in the form of compliance with technology, emission, or conservation standards. Thus, compared to the non-TCZ cities, it seems that land marketization significantly imposes more impact on eco-efficiency for TCZ cities. Our findings also indicate that land marketization in RB cities has a greater positive impact on ecological efficiency than that in non-RB cities. Similarly, policymakers in RB cities should make full use of the ecological effect dividend of land marketization to improve eco-efficiency and narrow the eco-efficiency gap between that of non-RB cities, and finally realize regional green development. Therefore, it is necessary to take differentiated policy measures according to local conditions in combination with the actual situation and specific environmental policies in each region.

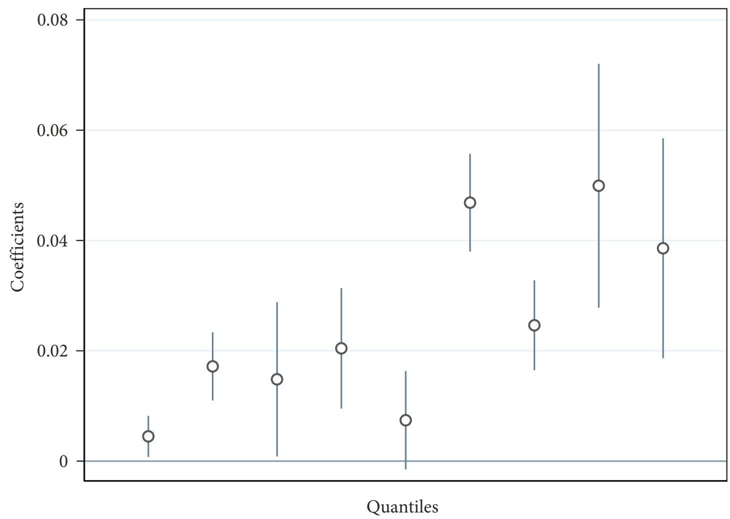


Figure 3. Heterogeneous effects across quantiles

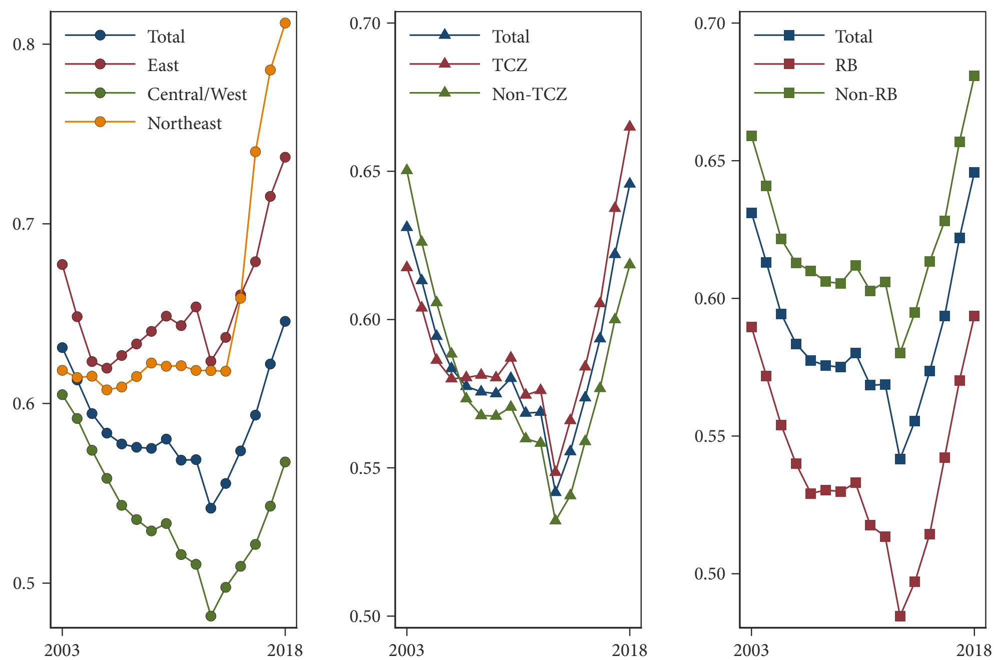


Figure 4. Evolution of eco-efficiency for different groups

Table 4. Heterogeneity analysis

Variables	By region			By environmental stringency		By resource policy	
	Eastern	Central/ Western	Northeastern	TCZ	Non-TCZ	RB	Non-RB
lm	–0.011 (0.629)	0.033** (0.022)	0.077 (0.138)	0.038** (0.012)	–0.002 (0.910)	0.034** (0.032)	0.011 (0.519)
control variables	YES	YES	YES	YES	YES	YES	YES
city fixed effects	YES	YES	YES	YES	YES	YES	YES
year fixed effects	YES	YES	YES	YES	YES	YES	YES
observations	1154	1960	269	1979	1404	1375	2008
adjusted R-squared	0.859	0.853	0.787	0.874	0.834	0.786	0.874

Notes: (1) Robust p value in parentheses and robust standard error are clustered at the city level. (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4. Spatial effects

The SLX model is estimated and its coefficients of β_1 and β_2 are analyzed. Figure 5 graphically illustrates the relationship between spatial spillover coefficient β_2 (left y-axis) and geographic distance variation. We find that the spatial effects of land marketization on eco-efficiency are significantly negative. For comparison, the estimation coefficients of β_1 (right y-axis) are also presented in Figure 5. The results show that the positive impact of land marketization on eco-efficiency is still significant when considering the spatial effects.

To sum up, we find that the land marketization of local city exerts significant positive impact on eco-efficiency. Meanwhile, peer cities with higher land marketization have a negative impact on the host city's eco-efficiency. Among peer cities in China, this shows that there are geographical spillovers and strategic competitions in land marketization among themselves.

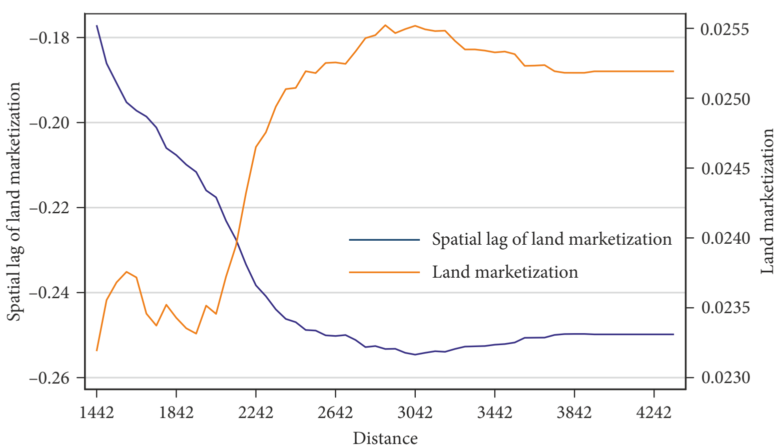


Figure 5. Distance effects of land marketization on eco-efficiency

3.5. Robustness checks

We also conducted a series of robustness tests on the above results. Table 5 presents the regression results.

First, following Cheng (2014), we utilize the Pearson correlation coefficient to determine the weights of input and output variables in NCMeta-US-EBM model. With the same scenario, we also measure eco-efficiency based on the directional distance function (DDF). Using these two alternative measures of eco-efficiency, we further estimate the coefficient of β in the baseline model. The results are shown in columns (1) and (2) of Table 5, indicating that the land marketization imposes significantly and positively effects on eco-efficiency. Specifically, one unit change in the *lm*, the eco-efficiency increases about 2.6%.

Second, we collect the land transfer area and land transfer transaction price from the *China Land* & *Resources Almanac*, and further calculate the two indicators to measure land marketization. Specifically, the land marketization is computed as the share of the land transfer area in total transfer area, and the share of the land transfer transaction price in total transaction price, respectively. Estimation results are presented in columns (3) and (4) of Table 5. The findings indicate that the baseline results are not depend on alternative measures of land marketization.

Third, following (Correia et al., 2021), we also estimate the baseline model using the Poisson pseudo-maximum likelihood regressions with multi-way fixed effects, as shown in column (5) of Table 5. The positive coefficient of *lm* indicate that the land marketization leads to an approximately 2.5% increase in eco-efficiency.

Table 5. Robustness checks

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ee_{usebmb}	ee_{usddf}				
lm	0.021* (0.060)	0.026** (0.040)			0.025*** (0.000)	0.041** (0.044)
lm_landarea			0.025* (0.074)			
lm_dealprice				0.023 (0.108)		
control variables	YES	YES	YES	YES	YES	YES
year fixed effects	YES	YES	YES	YES	YES	YES
city fixed effects	YES	YES	YES	YES	YES	YES
observations	3383	3383	3383	3514	3335	3383
adjusted R-squared	0.861	0.838	0.854	0.851	–	–
pseudo R-squared	–	–	–	–	–	0.023

Notes: (1) Robust p value in parentheses and robust standard error are clustered at the city level. (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (3) In column (5) the number of bootstrap replications is 2000 and Wald chi2 (267) is 21825.76.

Finally, the two bootstrap procedures are proposed for the two-stage efficiency estimation problem to improve inference (Simar & Wilson, 2007). We adopt the first algorithm proposed by Simar and Wilson (2007) for robustness check and the previous results are again confirmed as shown in column (6) of Table 5. Significantly, the key variable remains unchanged both in significance and sign. Thus, it can be empirically demonstrated that land marketization increases eco-efficiency.

3.6. Addressing the endogeneity

It is possible for policymakers and governors to recognize the consequences of land marketization and actively change the proportion of different types of land transaction based on the pollution emissions of industrial firms. This may lead to a reverse causality problem, resulting in the biased estimated results (Wang & Tan, 2020). Empirically, the Hausman test results also show that the IV regression is significantly different from the baseline regression, and the baseline model does have estimation bias caused by endogeneity problems. Given that, in this section, we apply the instrumental variable approach to address the potential endogeneity issue. On the one hand, we construct a Bartik (or shift-share) instrument (Goldsmith-Pinkham et al., 2020) based on variable *lm* and re-estimate the baseline model using a new econometric framework for shift-share instrumental variable regressions proposed by Borusyak et al. (2021). Estimation results are presented in column (1) of Table 6, indicating that land marketization has significantly and positively impact on eco-efficiency after addressing the endogeneity. On the other hand, following (Aladangady, 2017), we introduce the instrumental variable of the product of the benchmark interest rate in the current year and the undeveloped land area in the initial year (2001). The potential economic logic is that the undeveloped land area in the initial year will affect the way the government allocates land resources. The benchmark interest rate will affect the loan interest rate of local commercial banks, and further affect the land price. Because it is an important aspect that local governments need to consider when allocating land resources to obtain high land transfer income through unsaturated supply of commercial and residential land, the change of land price will inevitably change the allocation mode of local governments' land resources. Obviously, eco-efficiency cannot affect undeveloped land area in 2001. Meanwhile, the benchmark interest rate is the decision of the central bank or the higher-level central government, and the local economic behavior cannot influence it. The bank benchmark interest rate adopted in this paper is the one-year deposit benchmark interest rate published by the People's Bank of China. The undeveloped land area for each city in 2001 is calculated by ArcGIS software based on the 1:4 million topographic data of China, and then the area below 15 degrees of the city is subtracted from the built-up area of the city in 2001. Recently, this instrumental variable is also used by (Xie & Hu, 2020). Estimation results are summarized in column (2) of Table 6, indicating that the land marketization exerts significantly and positively effects on eco-efficiency. Both F statistics are much larger than 10, thus, the instrumental variables are relative valid. Given that, having considered endogeneity, the impact of land marketization on eco-efficiency is still significantly positive. The findings indicate that increasing the land marketization level is conducive to improving the quality of ecological environment.

Table 6. 2SLS estimation results

Variables	(1)	(2)
Panel A: Second-stage estimation		
lm	0.096** (0.042)	0.032** (0.019)
control variables	YES	YES
year fixed effects	YES	YES
city fixed effects	YES	YES
observations	2742	2803
R-squared	0.181	0.136
Panel B: First-stage estimation		
lm_bartik	1.406*** (0.000)	
baserateunder		0.395*** (0.005)
control variables	YES	YES
year fixed effects	YES	YES
city fixed effects	YES	YES
KP F-statistics	116.550	31.440

Notes: (1) Robust p value in parentheses and robust standard error are clustered at the city level. (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (3) *lm _bartik* represents the Bartik IV based on variable *lm*, and *baserateunder* denote the product of benchmark interest rate (at the national level and current period) and underdeveloped area (at the city level) in 2001.

4. Mechanisms

Eco-efficiency incorporates natural resources and ecological environment constraints into the framework of economic growth, and measures the net output capacity excluding the negative environmental externalities brought about by economic growth. Therefore, in the process of considering the potential mechanism and effect of land marketization on eco-efficiency, it can be analyzed from two aspects: one is how land marketization affects economic output capacity, and the other is how it affects environmental quality. If the coordinated development of the two can be achieved, then the eco-efficiency will be improved. This research framework lays the foundation for this paper to analyze the potential mechanism of land marketization on eco-efficiency. Therefore, the analysis of the mechanism of land marketization on eco-efficiency should not only consider the impact on environmental pollution indicators, but also take into account how land marketization promotes economic output capacity. Based on this, this paper decomposes the growth of eco-efficiency into: efficiency change, best practice change, and technology gap change. This section is dedicated to the analysis of how land marketization affects eco-efficiency, based on the tests that we conducted to estimate these impacts on efficiency change, best practice change, and technology gap change. These mechanism variables are measured by the Metafrontier-Malmquist model presented in section 2.2.

Based on the stepwise regression method proposed by Baron and Kenny (1986) and the mediation effect model (Shao et al., 2021), we further estimate how the land marketization level affects eco-efficiency through efficiency change, best practice change and technology gap change, respectively. The estimated results of the mediation effect model are presented in Table reported in Table 7. Regarding efficiency change, the land marketization has a significant positive effect of efficiency change, indicating that every one unit increase in land marketization level will cause efficiency change to increase by 1.3%, see column (2). In column (3), both *lm* and *efficiency change* are included in the baseline model. The results show that, *efficiency change* has significantly and positively associated with eco-efficiency. Specifically, the proportion of the land marketization on eco-efficiency attributable to *efficiency change* is about 16.67% (= [1–(0.020/0.024) × 100%]). Regarding *best practice change*, the land marketization also exerts a significant positive effect on best practice change, the findings show that every one unit increase in land marketization level will cause best practice change to increase by 1.2%, see column (4). Estimated results shown in column (5) indicate that, both *lm* and *best practice change* have significant positive effects on eco-efficiency. Moreover, the proportion of the land marketization on eco-efficiency attributable to *best practice change* is about 25% (= [1 – (0.018/0.024) × 100%]). While regarding technology gap change (see columns (6) and (7)), our findings indicate that the proportion of the land marketization on eco-efficiency attributable to *technology gap change* is also about 25% (= [1 – (0.018/0.024) × 100%]). In sum, we prove that efficiency change, best practice change, and technology gap change are the main channels and mechanisms for land marketization to affect eco-efficiency.

Table 7. Mechanism tests

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ee	*efficiency change*	*ee*	*best practice change*	*ee*	*technology gap change*	*ee*
lm	0.024** (0.043)	0.013* (0.061)	0.020* (0.078)	0.012** (0.045)	0.018*** (0.000)	0.013* (0.089)	0.018** (0.037)
efficiency change			0.037** (0.029)				
best practice change					0.139*** (0.000)		
technology gap change							0.069** (0.026)
control variables	YES	YES	YES	YES	YES	YES	YES
city fixed effects	YES	YES	YES	YES	YES	YES	YES
year fixed effects	YES	YES	YES	YES	YES	YES	YES
observations	3383	3169	3169	3169	3169	3169	3169
adjusted R-squared	0.854	0.503	0.907	0.492	0.904	0.432	0.904

Notes: (1) Robust p value in parentheses and robust standard error are clustered at the city level. (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Conclusions and policy implications

In this study, the effect of land marketization on eco-efficiency was investigated for 251 prefecture-level cities in China from 2003 to 2018. A sound understanding of how the land marketization affects eco-efficiency provides valuable insights into the trajectory of China's ecological sustainable development. In this paper, we first build a theoretical model to examine how the land marketization affect eco-efficiency and guide the empirical analysis. Theoretically, eco-efficiency could be positively affected by land marketization. Moreover, we propose a new DEA model which incorporated the non-convex metafrontier, super efficiency, and undesirable outputs into EBM to measure eco-efficiency. Given that, our empirical findings demonstrate that land marketization significantly improves eco-efficiency. Specifically, regarding the baseline results, an increase of 2.4% in eco-efficiency was associated with a 100% increase in the level of land marketization, *ceteris paribus*. This paper also investigates the heterogeneous effects of the land marketization on eco-efficiency across different quantiles, environmental stringency, and resource policy. In addition, the spatial effects of the land marketization on eco-efficiency are also estimated using the SLX model. The empirical findings are robust to alternative measures of eco-efficiency, alternative measures of land marketization, and alternative estimation methods. Besides, the endogeneity issues also discuss using IV approach. Finally, the mechanism analysis shows that land marketization mainly improves eco-efficiency by improving efficiency change, best practice change and technology gap change, respectively. These three channels and mechanisms approximately explain 66.67% of the impacts of land marketization on the improvement of eco-efficiency. The results provide new perspectives for the design of a land marketization reform policy for China.

Policy implications are outlined below based on the empirical findings. First, the increasing mode of urban eco-efficiency, which relies more on the incremental supply of urban land, is unsustainable. Therefore, the fundamental way to maintain the long-term and sustainable growth of urban eco-efficiency should be to continuously optimize and upgrade the level of land marketization based on the intensive and effective use of land resources.

Second, restrict the excessive supply of urban land, to force the improvement of urban land use efficiency, balance the land transfer income of local governments or enterprises and residents, and focus on restructuring the income distribution mechanism of urban land in the relevant system and policy regulation of land supply. It can be predicted that the stable and expected urban land system will bring more investment in urban land, make the capital stock per unit urban area grow continuously, and then improve the urban ecological environment with urban land as the material carrier to achieve more long-term development performance.

Third, we should continue to deepen the reform of land market, and implement differentiated development policies of construction land market according to the specific conditions of industrial industries in various regions. For example, while the developed cities along the southeast coast further improve the trading market of industrial land, they should also put aside the adverse effects of the rapid price increase of industrial land on the adjustment of industrial structure. However, cities in the central and western regions should keep the trend of slowly rising land prices, continue to give full play to resource advantages, and undertake the industrial transfer in the eastern and central regions, since the industrial transfer is conducive to mitigating carbon emissions. And this may further improve the ecological environment and eco-efficiency.

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Conflicts of interest

The authors declare no conflict of interest.

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